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From Sensors to Insights: A Review of IoT Applications in Soil Health Monitoring and Precision Farming

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Abstract

Soil health is a prerequisite for agricultural sustainability; however, the decline of soil health is a global crisis. Although conventional soil health analyses, reliant on laboratory methods, are reliable they are not time efficient, resource efficient and practical in terms of being timely for on-farm decision making. At the same time as the global food demand increases, resources become more limited, and climate change is necessitating an implementation of new technologies to monitor soil health in a continuous and scalable fashion. The Internet of Things (IoT) offers the opportunity to move to a new paradigm using low power sensors, wireless communication, cloud computing, and machine learning for agricultural applications. This synthesis will provide a summary of the state of soil health monitoring in reference to IoT applications. We will provide a brief overview of agronomically relevant indicators of soil health (physical, chemical and biological) of soil health and consider pertinent sensing technologies that will facilitate in situ measurement of these indicators and systems architecture as pertaining to IoT systems engineering / protocols and cloud computing will be evaluated for use in differing agricultural contexts (i.e., large scale commodity agriculture, smallholder, etc.). The farm case studies examined from cases around the globe serve as an applied representation of how IoT initiatives can lead to savings in water, nutrient use efficiency, and/or yield improvements. Although successful, the case studies are not without challenges associated with sensor drift, communications delays, power capabilities of sensors and sensors as equipment cost, and farmers willingness to adopt. This synthesis will conclude with some future directions of edge artificial intelligence, block chain enabled data fidelity, and digital twins (models) for agricultural environments in real time context.

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1. Introduction

Soil is widely considered to be the foundation of terrestrial life; it not only anchors plants in place it is also a living system that contributes to water regulation, nutrient cycling and storage, habitat for biodiversity, and agricultural support. Soil health is described as the physical, chemical, and biological properties of soil in order to function as needed for food system provision, ecosystem service provision, and environmental adaptability [4]. The importance of soil health is not lost on a global scale, with the Food and Agriculture organization estimating at least 33% of soils globally are at least moderately to highly degraded. The causes of degradation include nutrient depletion, acidification, salinization, erosion, deforestation, and over-intensification of cropping intensity [23]. The decrease in soil quality will threaten food security directly, especially in a world that is projected to have nearly 10 billion humans by 2050. Traditional soil testing - in a laboratory, soil testing of soil samples to test pH, electric conductivity, macro- and micronutrients - are accurate, but slow, costly, and not spatially or temporally frequent [10]. Farmers can wait days to weeks between sending samples and receiving recommendations, which may hinder their capacity to respond to changes in soil conditions related to rain, irrigation, or management practices. Thus, there is an immediate urgency for an even real time and scalable soil monitoring systems that are proactive [2].

Soil health monitoring is poised to increase in importance as new technologies advance. The Internet of Things (IoT) is changing the paradigm of how agricultural data is collected, transmitted and analysed. The IoT is an interconnected system of objects or material devices that are equipped with sensors, processors and communication modules that can sensorially collect information from its surrounding environment and send the data back to local gateways or remote servers for processing [5]. In agricultural applications, the IoT systems have evolved from having single point weather stations into many sensors in a distributed multi-sensor system that tracks soil moisture, nutrient status, temperature, and even biological signals. By adding sensors to the soil along with wireless communications protocols and cloud systems, a farmer will monitor soil health status right on their mobile device, amend irrigation on the sport, or be alerted on nutrient deficiency long before plant stress is visible [6]. Precision nutrient application will limit over fertilization, limiting nitrate leaching and to ground water. Timely irrigation scheduling will conserve water in water-limited areas. Real time monitoring can detect salinity build up before causing long term soil loss. At a high-level, utilizing IoT to monitor soil health aligns with many of the sustainable development goals (SDGs) for food security, clean water, climate adaptation and responsible production & consumption [31].

Many proofs of concepts, testbeds, and pilot studies have been conducted over the last decade to identify the potential for IoT to monitor soil health; however, actual implementation has been sluggish from pilot projects to commercial systems. Sensor drift, gaps in communication coverage, finite battery life, data interoperability, and cost are barriers for widespread

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implement. At the same time, smallholder farmers—whom are the most susceptible to soil degradation, have many barriers to access technology in the form of cost and recognition of the potential. Therefore, after exploring the potential uses for IoT for soil health, it is necessary to consolidate to content to offer a review of what has been done, what barriers exist, and what opportunities there are next [19].

2. Soil Health Indicators & Parameters

Soil health is an encompassing term that incorporates variables that influence biological, chemical and physical characteristics that are ultimately what defines the soils' ability to sustain crop growth, mitigate the environment, regulate water cycles, and support carbon cycling. When designing an IoT application, the soil health indicators are extremely important because they determine the sensors that need to be used, the frequency of sampling and the analytical methods the sensors could generate [2] [5].

2.1 Physical Indicators

Soils physical attributes also affect the plants access and uptake of water and oxygen, the ability for roots to penetrate through the growing medium and the physical structure of soil supports crops. Some of the soil physical attributes are soil moisture content which is most likely the most referenced parameter in IoT applications. Soil moisture is a direct measurement parameter, appropriate timing and water efficient irrigation will be a challenge. Gravimetric moisture levels are precise, but scale is not economically feasible. Capacitive and resistive sensors measure in a capacitive manner; therefore, it is a near real-time measurement [9]. Soil temperature tells the effects soil microbial processes, nutrient mineralization, and crop depth germination timing. Thermistors and sensing probes allow for continuous capture [13]. Porosity and bulk density lets us know how it relates to aeration and water holding capacity, however as measured with IoT data, is hardly used due to the challenge of sensor discovering bulk density and porosity. Modelling can possibly be leveraged to eventually come up with an indirect estimate for density and porosity.

2.2 Chemical Indicators

The chemistries of soil impact nutrient availability and crop productivity includes soil pH. The optimal pH range when growing crops is from pH 6.0 – 7.5, crops can also be grown outside this range if they are adapted to acidic or alkaline conditions. Modern IoT platforms use ISFET pH sensors, which are ion sensitive field effect transistors, which durability makes them appropriate for long term instant deployment [17]. Electrical Conductivity (EC) can be a proxy for fertility and salinity. A high EC reading indicates either soil development or salt build-up [12]. Soil macronutrients (NPK) include nitrogen, phosphorus and potassium are essential macronutrients for biomass growth. A need for the in-field monitoring of these macronutrients using IoT based ion selective electrodes (ISE) and optical sensors is in progress [5]. Soil Organic Matter (SOM) tells how soil possesses cation exchange capacity which allows soil to

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hold water. There are spectroscopic sensors like portable NIRs that can offer a rough estimate of SOM in the field [15].

2.3 Biological Indicators

Biological indicators evaluate the “living” component of soil and these are being further examined in IoT applications are microbial biomass & respiration. It indicates soils metabolic activity and potential capacity for nutrient cycling. It is difficult to assess in situ, but bio sensors represent a new avenue of research. Soil enzyme activity gives dehydrogenase which is an example of an enzyme that indicates microbial metabolic functioning. Some optical sensors can estimate enzyme activity in an indirect way. Soil fauna tells that earthworm population assessments are still manual, but in the future could be supplemented with imaging IoT systems.

Table 1. Key Soil Health Indicators and Measurement Approaches

Indicator	Category	Role in Soil Health	Traditional Method	IoT-based Sensor/Tech
Moisture Content	Physical	Water availability & irrigation	Gravimetric method	Capacitive / Resistive probes [9]
Temperature	Physical	Enzyme activity, germination	Mercury/digital thermometer	Thermistor probes [13]
Bulk Density	Physical	Soil compaction	Core sampling	Estimated by model integration
pH	Chemical	Nutrient solubility & availability	Glass electrode	ISFET pH sensor [17]
Electrical Conductivity	Chemical	Salinity and fertility indicator	Salinometer	EC probes [12]
N, P, K Nutrients	Chemical	Primary macronutrients	Laboratory extraction	Ion-selective electrodes [5]
Organic Carbon	Chemical	Soil quality & carbon sequestration	Wet combustion assay	NIR spectroscopy [15]
Microbial Biomass	Biological	Indicator of biological activity	Fumigation-extraction	Biosensors (R&D) [14]
Enzyme Activity	Biological	Soil metabolic health	Colorimetric test	Optical enzyme sensors [19]

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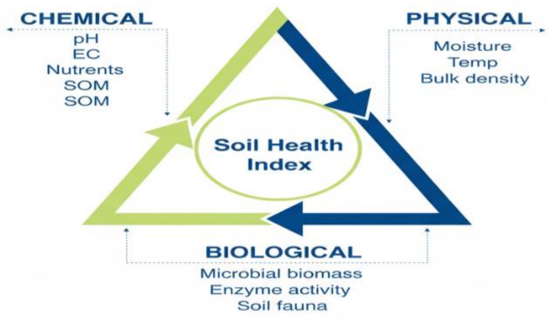

Figure 1. Integrated View of Soil Health Indicators

The following diagram provides an integrated view of the physical, chemical, and biological components that collectively define soil health. Figure 1 illustrates how different soil parameters interact dynamically, influencing soil functionality and supporting ecosystem services critical for sustainable agriculture

2.4 The Soil Health Index (SHI)

Contemporary frameworks leverage individual measurements into a composite Soil Health Index (SHI) or scoring framework [8]. Algorithms utilize moisture, pH, EC, nutrient concentrations, and organic matter to compute a weighted index that simplify farmers' decision-making processes. IoT platforms improve the SHI by making data collection automatic and continuously updated rather than each year or seasonally.

2.5 Aligning Indicators with IoT

For those adopting IoT, parameter selection is strategic. While not needed to realistically monitor every single possible parameter simultaneously, the majority of IoT deployments focus on core parameters related to cluster (moisture, pH, EC, NPK, temperature) and grew with much higher correlation. If biological factors are analysed, they are still more research-related than operational.

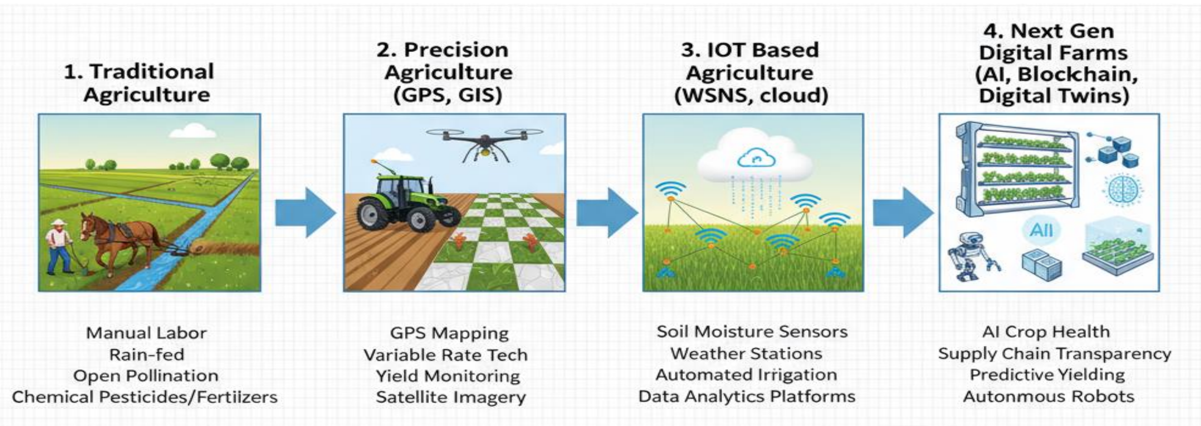

Figure 2. Transformation Pathway of Agriculture Through IoT

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The transformation pathway of agriculture through IoT technologies can be visualized as a stepwise integration of sensors, connectivity, analytics, and decision-making. The pathway in Fig.2 demonstrates the shift from conventional manual soil assessment methods toward data-driven smart agriculture enabled by IoT infrastructure.

3. Sensors for Soil Health Monitoring

3.1 Soil Moisture Sensors

The most widespread measurement for IoT deployments is soil moisture. The principle consists of:

3.1.1 Resistive Sensors measured alterations in electrical resistance as the water content altered the soil's electrical conductivity; they are cost-effective but are susceptible to corroding and interference from salts; and are suitable for smaller scale study but longevity will impact their accuracy in the long run [9].

3.1.2 Capacitive Sensors are reliant on the change in dielectric permittivity of the soil; they are quite stable sensors and useable in a field scale IoT method; they do require proper calibration for the soil texture [6].

3.1.3 Time Domain Reflectometry (TDR) sensors are precise due to decoding the reflected electromagnetic waves as they travel through the probes, they are the most accurate sensor, but most expense and use a fair deal of energy to operate so are not able to run for the low cost IoT [17].

3.2 Soil pH Sensors

Soil pH has major effects on nutrient availability and microbial activity. Glass electrode pH sensors refers to traditional laboratory standards and applied to the field probe. Ion sensitive field effect transistors (ISFETs) let us know the reduced drift compared to glass electrodes allowing long-term deployment of sensors [11].

3.3 Nutrient Sensors

Real time measurements of nitrogen (N), phosphorus (P), and potassium (K) are an important aspect of precision agriculture, though challenging to achieve.

3.4 Electrical Conductivity (EC) Sensors

EC is indicative of salinity and overall ionic makeup. Simple stainless steel EC probes are typical in IoT soil kits [12]. IoT kits commonly combined EC with moisture since there is a strong relationship between the two.

3.5 Temperature Sensors

Thermal properties of the soil dictate germination and other enzymatic and biological processes. These sensors are robust, inexpensive thermistors or digital sensors, which also work

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well with microcontrollers. Temperature sensors have become routine in IoT agricultural nodes [20].

3.6 Organic Matter & Carbon Sensors

Soil organic matter (SOM) dictates nutrient holding capacity and resilience. SOM has historically been measured using wet chemistry, but near infrared (NIR) IoT type devices are becoming available for in situ assessments [14]. There have been studies on wheat and corn systems in which NIR passes correlated with SOM, but they must still be calibrated to site specific conditions.

3.7 Biological Health Sensors

Much of the use of IoT for soil biology applications are still experimental. Biosensors use genetically engineered microbes or microbial enzymes that produce electrical signals indicating microbial function [18]. Indirect IoT capture uses temperature, moisture and organic carbon to create the mathematical models of respiration or microbial function

Table 2. Comparison of Soil Health Monitoring Sensors

Sensor Type	Parameter	Principle	Accuracy / Resolution	Cost	Energy Demand	Advantages	Limitations	References
Resistive Moisture	Moisture	Soil resistance	±5–10% vwc	Very Low	Medium	Very cheap; easy integration	Corrosion, salinity effects	[9]
Capacitive Moisture	Moisture	Dielectric permittivity	±3% vwc	Low	Low	Stable, low power	Needs calibration by soil type	[6]
TDR Probe	Moisture	EM pulse reflection	±1% vwc	High	High	Very accurate	Expensive, high energy	[17]
Glass Electrode pH	pH	Potential difference	±0.05 pH	Med	Medium	Highly accurate	Fragile, calibration drift	[11]
ISFET pH Sensor	pH	Solid-state transistor	±0.1 pH	Med-High	Low	Durable, IoT-friendly	Higher cost, needs periodic cal.	[11]

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Ion-Selective Electrode	NO3−, K+	Ion exchange membrane	±5% conc.	Med	Med	Direct nutrient detection	Selectivity issues; calibration	[5]
Spectroscopy (NIR)	SOM, NPK	Optical reflectance	$R^2 > 0.85$ (SOM est.)	High	Med	Rapid, multi-parameter	Needs calibration sets	[14] [16]
EC Probe	Salinity	Conductivity measurement	±0.2 dS/m	Low	Low	Easy deployment	Temp. dependent corrections	[12]
Thermistor	Temp	Resistance-temperature	±0.2 °C	Low	Very Low	Rugged, cheap	Only point-based data	[20]
Biosensor (Experimental)	Microbial biomass	Bio-reactions	Relative units	High	Med	Biological insight	Not standardized for field yet	[18]

(Abbreviations: vwc = volumetric water content; SOM = soil organic matter)

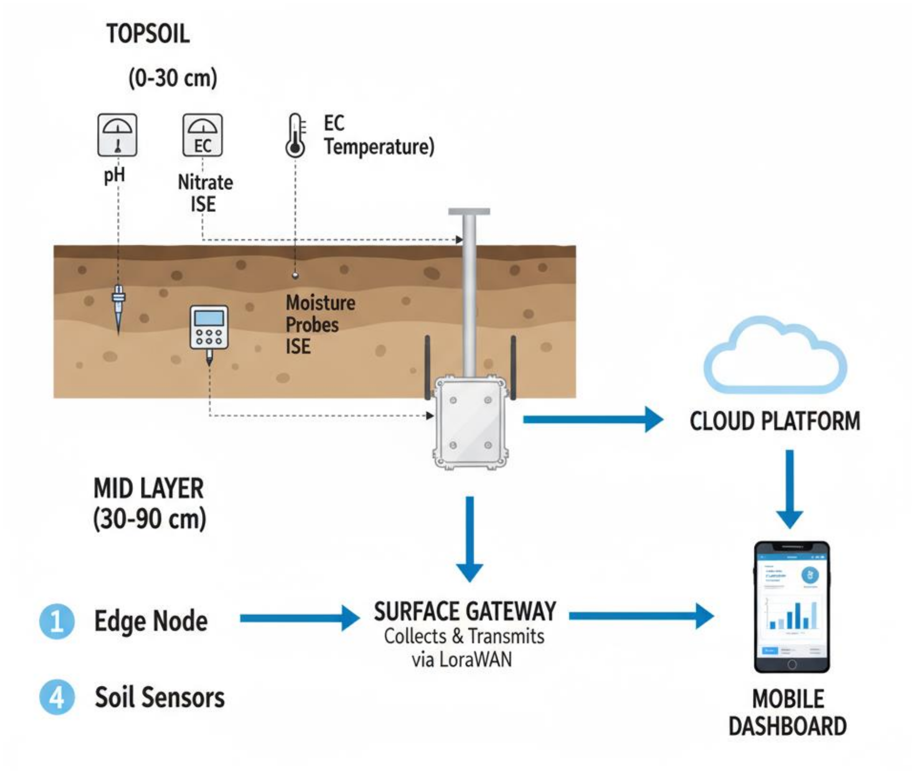

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Figure 3. IoT Soil Sensor Deployment

The deployment of IoT-based soil sensors involves strategic placement across farm plots to capture diverse soil conditions. Figure 3 shows the spatial arrangement of soil sensors, data flow through gateways, and connectivity mechanisms that ensure real-time soil monitoring.

Soil monitoring in the IoT context will have various sensors as the range of sensors is evolving and extending with differing agronomic trade-offs of price, accuracy, and robustness. Most commercially available sensors are moisture and temperature sensors while nutrient and biological sensors are a novel future area for disruption [5] [18]. The next section outlines how the selected sensors will all be connected using specialized IoT architectures that you can utilize for soil health monitoring.

4. IoT System Architecture for Soil Health Monitoring

An IoT ecosystem for soil health monitoring is not simply sensors. Rather, it is a layered system, where the combined sensing, communicating, processing and exploitation components effectively transform measurements in the soil into actionable agricultural intelligence [2] [6]. The structuring and configuring of this architecture is paramount for achieving scalability, reliability, and energy efficiency in operation, especially when deployed in real farm environments.

4.1 Layered Model of IoT in Soil Monitoring

A majority of frameworks use a four layered model similar to traditional IoT deployments in other fields [11]:

4.1.1 Perception Layer (Sensing): All soil monitoring sensors (e.g., moisture, pH, NPK, EC, temperature, biological) fit into this category. These sensors are often located in the root zone (10–30 cm depth), sampling values at intervals. Often the sensors have microcontrollers with analogue to digital converters and local firmware for pre-processing [12].

4.1.2 Network Layer (Communication): The type of technology is based on the scale of farm and connectivity options: LoRaWAN for remote, low power long distance systems, NB IoT for mobile operator type systems, ZigBee for a greenhouse IoT cluster [9] [14].

4.1.3 Application Layer (User Interfaces): Dashboards and mobile apps provide soil status in real time, composite Soil Health Index (SHI) scores, irrigation recommendations, and alerts on fertilizer adjustments. Alerts are often created with thresholds established by individuals exercising agronomic expertise [16].

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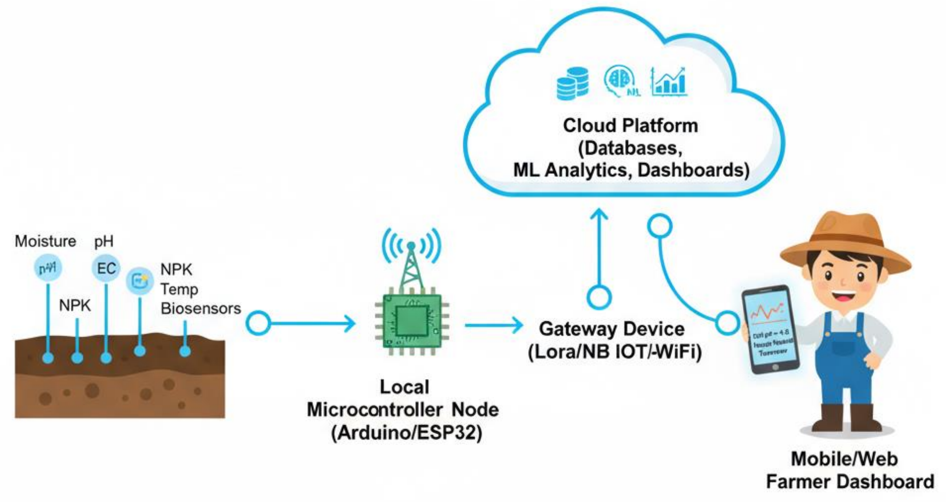

Figure 4. IoT Soil Monitoring Architecture

The IoT architecture for soil monitoring typically follows a layered structure for efficient sensing, data transmission, and analysis. Figure 4 highlights the four-layered IoT architecture—perception, network, middleware, and application layers—each responsible for transforming raw soil data into actionable agricultural insights

4.2 Edge vs. Cloud Processing

Traditional IoT systems were flooding directly send soil sensor data to the cloud where mini-delays occurred with every data point sent to the cloud. In rural areas with limited bandwidth, this was inefficient. Edge computing (process data much closer to the field on gateways) has become more common. Benefits include lower delay, decreased bandwidth utilization; better independence of your internet drops [13]. Example a Spanish vineyard IoT system use location processing soil moisture data to process irrigation start/stop decisions helping to lower bandwidth by up to 60% [14].

4.3 Data Flow and Security

The sequence of data typically follows:

Acquisition→ Preprocessing→ Transmission→ Storage→ Analytics→ Decision Support.

It is evident that security is important because soil data can contribute to agricultural planning on a government level. IoT installations are relying more on light weight encryption algorithms (e.g. Elliptic Curve Cryptography, AES 128) suitable for low power microcontrollers [18].

4.3 Integration with Other Systems

4.3.1 IoT enabled Pump: Activated according to soil thresholds.

4.3.2 Remote Sensing Data (Drones, Satellites): Verifies sensor readings over a large area [19].

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The integration makes soil IoT architecture part of a digital farming ecosystem that could send a signal to a more comprehensive farm management information system (FMIS).

Table 3. IoT Architecture Layers and Functions in Soil Monitoring

Layer	Components	Functions	References
Perception	Soil sensors (moisture, pH, EC, NPK, temp, biological)	In-situ data collection, analog signal digitization	[12]
Network	LoRaWAN, ZigBee, NB-IoT, Wi-Fi, LTE-M	Transmit data from nodes to gateway/cloud	[9] [14]
Middleware	Edge gateways (Raspberry Pi, ESP32), Cloud servers	Preprocess/filter data, store, apply ML models	[13] [15]
Application	Dashboards (mobile/web), SHI visualizations	Farmer decision support, irrigation alerts	[16]

4.4 Studies Done In Different Locations:

4.4.1 LoRaWAN enabled maize field (India): On a maize field in India where integrated soil moisture sensors send data to a cloud dashboard, irrigation water was reduced 37% without yield loss [2].

4.4.2 NB IoT in Dutch Greenhouses: pH and EC sensors connected to cloud processing that automated fertigation. Crop yield increased 12% over manual scheduling [6].

4.4.3 Community Owned IoT Architecture in Kenya: Farmers contributed money to purchase gateways to situate distributed soil sensing for villages to cooperate [19].

The IoT soil monitoring architecture is multi-layered in nature, and distributes the processes of collecting data, transmitting data, processing data, and communicating with farmers. The emerging architecture is more frequently hybrid, and incorporates edge processing, secure cloud analytic, and easy to interface visualization. Sensors, communications, and cloud-based intelligence are the three corners forming the current IoT soil ecosystem. The next section will look closely at the communication protocols in the networks layer of these architectures.

5. IoT Communication Protocols for Soil Monitoring

The communication protocols that are utilized by IoT devices are the means of communicating soil information from distributed fields to gateways, servers or cloud services. In contrast to industrial or urban IoT applications, agricultural deployments are typical in rural, resource-limited, and remote areas where power, coverage and cost intently matter [6] [11].

5.1 Short Range Protocols

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5.1.1 ZigBee / IEEE 802.15.4. Constructs mesh network – Great for greenhouses and small fields. Each "node" passes the signal along, and range is extended. Not useful in large areas unless many nodes are built, lots of signal can diminish. [14].

5.1.2 Bluetooth Low Energy (BLE) – great for farmer to sensor communication with a smartphone. Good for small hand testing devices, low range (10-50 m).

5.1.3 Wi Fi – provides high data rates which laptops and video and/or wireless camera(s) can be utilized in the process. However, the energy requirements are too high, and it has to be initialized with high amount of initial charging so therefore, not suitable for farm-based operations [16].

Table 4. Comparative Study of Communication Protocols in Soil IoT Deployments

Protocol	Typical Range	Data Rate	Power Demand	Deployment Cost	Pros	Cons	References
LoRaWAN	2–15 km rural	0.3–50 kbps	Very Low	Medium (gateway needed)	Long range, battery life 5+ years	Low throughput for images	[12]
Sigfox	10–40 km rural	100 bps	Ultra Low	Low-Medium	Extremely energy efficient	Payload limits, operator dependent	[18]
NB-IoT	2–10 km (cell)	30–250 kbps	Low	Medium-High	Reliable via mobile networks	Subscription fees, network reliance	[20]
LTE-M	1–5 km (cell)	300 kbps–1 Mbps	Medium	Medium-High	Higher throughput, mobility support	Higher power use, still costly	[20]
ZigBee	10–100 m	20–250 kbps	Low	Low	Mesh support, cheap devices	Limited coverage without many nodes	[14]
Wi-Fi	50–100 m	1–100 Mbps	High	Low	High bandwidth, broad familiarity	Short range, drains energy quickly	[16]

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Protocol	Typical Range	Data Rate	Power Demand	Deployment Cost	Pros	Cons	References
BLE	10–50 m	125 kbps–2 Mbps	Very Low	Very Low	Smartphone connectivity	Not scalable to large fields	[19]

5.2 Hybrid Protocol Approaches

Multiple experimental implementations meld protocols together.

5.2.1 ZigBee + LoRaWAN: ZigBee mesh does granular, intra farm soil data acquisition; LoRaWAN moves the aggregated packets to the cloud [9].

5.2.2 Wi Fi + Edge Node: By using high bandwidth Wi Fi between sensors and edge (i.e. Raspberry Pi), and LoRaWAN or LTE M for the backbone uplink [13].

5.3 Security and Reliability in Soil IoT Networks

Communication protocols should also facilitate data integrity and resiliency. Simple lightweight secure implementations such as AES 128 for LoRaWAN encrypt sensor readings. Redundancy (deploying overlapping nodes) provides reliability and buffering of data in gateways help avoid packet loss when a connection is absent [17].

There is growing research interest in the use of blockchain technologies with IoT networks offering guarantees of tamper proof logging of soil data packets for transparency and certification [15].

Effective soil IoT implementation depends on choosing the right communication technology according to range, bandwidth, and energy constraints

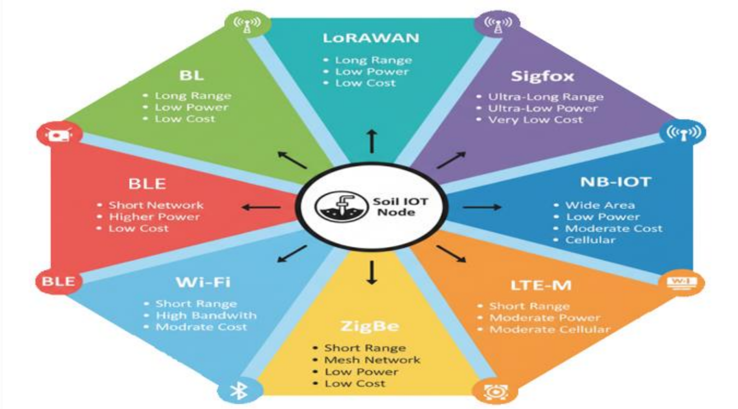

Figure 5. Communication Options for Soil IoT

Effective soil IoT implementation depends on choosing the right communication technology according to range, bandwidth, and energy constraints. Figure 5 compares various wireless

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communication options used in agricultural IoT, emphasizing the trade-offs among range, data rate, and power efficiency

The context, when determining a communication protocol in agricultural Internet of Things (IoT), matters. In large rural farms where no infrastructure exists, typically LoRaWAN and Sigfox, with its long range and low power, is the go-to. Greenhouses and peri urban field may leverage ZigBee or WiFi. If acceptable mobile infrastructure is available, NB IoT and LTE M can be installed, but costs are higher. For the purpose of growing and sustaining soil health, IoT implementation is more and more using hybrid strategies for coverage, power, and reliability [9] [12] [20].

6. Cloud Computing and Data Analytics

The rapid proliferation of IoT nodes (sensors) in agriculture also leads to an enormous volume of readings. A typical deployment of soil sensors, for example, with 50 nodes providing readings every 10 minutes would lead to over seven million records over the course of a year [6]. The high-frequency, highly heterogeneous data, as described above, comes with the need for a considerable cloud, and analytic architecture. This is because cloud platforms can provide a more flexible resource for ingestion, storage, processing, visualization, and decisions [12]. Additionally, an edge analytics component may be applied along the chain to try and reduce latency and bandwidth requirements.

6.1 Agricultural Data Characteristics

The soil sensor data from the IoT can present some very unique challenges:

Heterogeneous: Different units, sampling rates, and all the parameters (moisture %, pH, nitrate mg/kg, EC dS/m).

6.1.1 Spatial correlation: Soil properties can vary significantly over very short distances, thus some spatial statistics (kriging, geo-statistics) will be needed [10].

6.1.2 Temporal variability: Soil moisture can vary rather widely from hour to hour, nutrients can vary from season to season [19].

6.1.3 Quality issues: Gaps in some data due to lost connections, or sensor drift might require cleaning and imputation algorithms [14].

6.2 Cloud Platforms for Soil IoT

The main platforms that are providing IoT agricultural support are:

6.2.1 AWS IoT Core + Amazon Timestream: Real time, time series ingestion, with anomaly detection.

6.2.2 Microsoft Azure FarmBeats: Combines agronomic IoT data with satellite imagery and machine learning integrations and farmer dashboards [9].

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6.2.3 Google Cloud IoT + BigQuery: Provides scalable analysis and visualization.

6.2.4 Opensource (ThingsBoard, Node RED): Mostly used for low-cost projects and academic prototypes.

Table 5. Cloud and Edge Solutions for Soil Monitoring IoT

Platform	Type	Features	Cost Model	Example Application	Reference
AWS IoT Core + Timestream	Commercial	Time-series DB, alerts, analytics	Pay-per-use	Soil EC anomaly alerts for orchard farms	[12]
Azure FarmBeats	Commercial	Fusion of IoT + satellite imagery, AI models	Subscription	Fertilizer optimization in India	[9]
Google Cloud IoT + BigQuery	Commercial	Machine learning integration, data pipelines	Pay-per-use	Irrigation optimization (Spain)	[15]
ThingsBoard	Open Source	Customizable dashboards & rule engines	Free / On-prem	Smallholder LoRaWAN trials in Kenya	[19]
Node-RED + InfluxDB	Open Source	Local edge analytics, visual flow programming	Free	Vineyard irrigation optimization	[14]

6.3 Analytics Pipeline

The processing of soil data is done in iterative steps [6] [17]:

6.3.1 Pre Processing: Filter out noise (i.e., batteries are in the soil at unreasonable pH < 2). Machine Learning Models, e.g. Predicting irrigation windows and finding fertilizer deficiency areas. Decision trees are the simplest forms of algorithms but support vector machines as well as deep neural networks Broad [16].

6.3.2 Visualization & Alerts: In order to present the information to the farmer, the system displays heat maps, time series plots and SHI indicators in dashboards and eventually SMS alerts.

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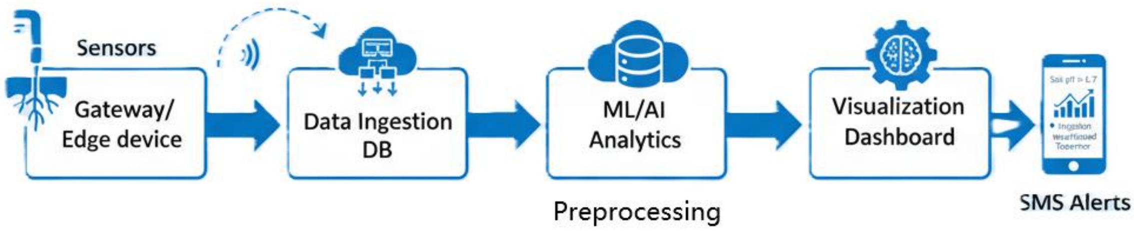

Figure 6. Soil IoT Analytics Pipeline

After data collection, IoT-based soil monitoring systems use an analytics pipeline to convert raw data into meaningful agronomic insights. The diagram in Fig.6 outlines each processing stage—from acquisition to decision support—showing how pre-processing, machine learning, and visualization tools aid farm management

6.4 Edge Analytics and Edge AI

Sending all unprocessed data to the cloud is not a sustainable use of connectivity. Edge computing allows information to be processed at the nodes and summary information sent to the cloud. Example there was a greenhouse IoT edge node that was able to determine when to irrigate locally, and sent only the "Pump ON/OFF" event, meaning only 15% of the data was sent to the cloud in the end [14]. Edge/AI includes lightweight models (Tiny ML, TensorFlow Lite Micro) running locally on an ESP32 or STM32 microcontroller, have also been demonstrated on-farm to make pest/drought predictions even without any internet connection [20].

6.5 Decision Support Dashboard

User interfaces are paramount for the end users:

6.5.1 **Visualizations:** Multiparameter plots (e.g. nitrate vs time); Soil spatial maps (yet enter GIS analysis and data fusion) [19].

6.5.2 **Alerts:** Provide SMS/WhatsApp (simple processing and mobile) irrigation recommendation directly to the farmer, for example [19].

6.5.3 **Composite indices:** An automatic Soil Health Index (SHI) could be formed from pH, EC, moisture, and organic matter [8].

The cloud and analytics layers make analyses of soil IoT data actionable agronomy. combining edge processing with the cloud analytics layer using AI models makes modern solutions more than just data logs and analytics with actionable intelligence. The issues are always costs, rural connectivity, and generalizability of the models is still a challenge [10] [16] [19].

7. Literature Review

Although theoretical frameworks and experimental prototypes show the potential of the IoT in soil health monitoring, all actual field implementations are necessary to confirm reliability,

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farmer acceptance, and long-term effects. In the last 10 years, pilot projects and research case studies have been developed around the world, from high input, technology developed systems in developed economies to low-cost community-based solutions in developing regions.

7.1 Vineyards in Spain (LoRaWAN + Edge Analytics)

In Spain's Mediterranean region - a water-scarce region - vineyards are further challenged. Never the less, the project demonstrating a LoRaWAN based soil moisture IoT system was conducted by Ferrández Pastor et al. [14], on vineyards across fifty hectares.

7.1.1 **Setup:** Capacitive moisture probes are installed at three depths (10, 30, 50 cm), with LoRa nodes relaying telemetry to gateways.
7.1.2 **Analytics:** Edge devices provided real time irrigation triggers corresponding with adaptive threshold models.
7.1.3 **Outcomes:** 32% less water was used, and quality of grapes improved with advances on the optimal soil moisture stress threshold.
7.1.4 **Farmer Impact:** Farmers used mobile applications to access dashboards and it was estimated 80% of cooperative members would adopt it.

7.2 Rice Paddy Fields in India

In the state of Tamil Nadu in India, soil nutrient and water management research was funded to test IoT for precision irrigation in paddy growing areas [2].

7.2.1 **Set up:** Moisture and nitrate sensors using ESP8266 boards and wirelessly transmitting to cloud dashboards over Wi Fi.
7.2.2 **Outcome:** Exceeded target of providing 15 % less application of fertilizer and 22 % less irrigation water compared to normal practices.
7.2.3 **Farmer benefit:** Yield remained constant while saving on input cost led to net income increase of approximately 10 %.

7.3 Dutch Greenhouses (NB-IoT Controlled Fertigation)

More aggressive use of the IoT in protected cultivation systems in the Netherlands. In the study [6]:

7.3.1 **Setup:** NB IoT devices monitored pH and EC of hydroponic soil media.
7.3.2 **Integration:** Cloud based fertigation system adjusted the nutrient solution mix in real time.
7.3.3 **Outcome:** Increased tomato yield by 12% and 20 % less waste of nutrient solution.

7.4 Kenyan Smallholder Farms (Community Architecture)

African smallholders are faced with outreach costs that make proprietary IoT kits untenable. A research pilot that is located in Kenya country [19]:

7.4.1 **Setup:** open source LoRaWAN kits (Arduino + low-cost probes). A community cooperative invested in one communal gateway for the group.

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7.4.2 **Outcomes:** 25 smallholder farmers could monitor, collectively, moisture over 100 hectares of land.

7.4.3 **Impact:** 20% savings of water on maize fields, and strong knowledge transfer through use of common dashboards.

7.4.4 **Importance:** Highlighted that cooperative ownership models can on ramp IoT capability for resource limited communities.

7.5 IoT-Cloud Integration for Soil Salinity (China)

Coastal agricultural areas of China are frequently threatened by secondary salinization. Zhang et al. [9]: Set up involves salinity probes took readings transmitted via ZigBee to various gateways, and then to cloud dashboards. In the end, farmers received real time alerts about salinity levels, and there were <15% losses in vegetable production due to salinization intrusion.

Table 6. Highlights of Global IoT Soil Monitoring Case Studies

Region / Country	Cropping System	Sensors Used	Comm. Protocol	Key Results	References
Spain	Vineyards	Moisture probes	LoRaWAN	32% water saving, improved grape quality	[14]
India (Tamil Nadu)	Rice paddies	Moisture, nitrate	Wi-Fi	15% less fertilizer, 22% less water	[2]
Netherlands	Greenhouse tomato	EC, pH sensors	NB-IoT	12% higher yield, 20% resource saving	[6]
Kenya	Maize (smallholder)	Moisture probes	LoRaWAN	20% water saving, community adoption	[19]
China (Coastal)	Greenhouse veg	EC probes	ZigBee	Reduced salinity yields by 15% loss	[9]

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Figure 7. Geographic Distribution of IoT Soil Monitoring Case Studies

The degree of uptake of IoT-based soil health systems around the world has a large geographical and farming system variation. Figure 7 shows where the examples from the case studies presented in this paper are located around the world with examples being used everything from vineyards in Spain, rice paddies in India, and community farms in Kenya.

7.6 Trends Are Observed

Water Savings Are the Biggest Early Impact: In irrigation studies in the majority of the sites described reduced the amount and use of irrigation resources from 15-40% in some cases. Fertilizer Optimization- This is emerging. Real-time nutrient monitoring is not common at this stage but the authority around this use is becoming more and more validated. Scale Matters: The high-income context predominantly uses proprietary systems. The low-income context tends to modify an open-source system with the support of the community [19]. Integration Is Desired: There is a growing wish in projects to see an integration of estimates from sensor data - soils, weather forecasted, drone images, controlled irrigation. Farmer Engagement Matters: In projects where the farmers could access dashboards in their own language there was increased uptake and trust [10].

7.7 Lessons learned

In terms of the case studies, some context appropriate lessons are available - it is recognized that IoT deployments need to be context appropriate (e.g., rural areas - LoRaWAN, peri-urban greenhouses - NB IoT). Open-source community models are very good in providing for smallholder farmers who may be capital-strained. For sustainability long-term, these also require maintenance, calibration of sensors, and training in the devices.

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Consistently, in real world case studies, outcomes show that IoT improves efficiencies water and nutrient use as well as stabilizes yields, and positively impacts the farmers profitability. However, these outcomes could be contingent on sustaining socio-economic contexts, infrastructure of use, and most importantly farmer engagement. These lessons will be helpful in providing direction to future large-scale deployments.

8. Challenges and Limits

IoT based soil monitoring has great promise for changing agriculture; however, many challenges remain. They happen along the entire technology stack from the sensor hardware to the underlying network, and socio-economic and governance issues. Understanding these challenges will be key for producing large scale, efficient and sustainable deployments [6, 10].

8.1 Sensor Related Challenges

8.1.1 Calibration and Drift

Soil is heterogeneous; all properties (pH, salinity, texture, moisture) vary in scale over meters and minutes. These natural variations means that there will be a calibration target that is always moving (pH sensors and ion selective nutrient probes can drift in readings also) [5]. Without calibration and managing for drift, raw IoT data can lead to poor decisions leading to poor soil management.

8.1.2 Durability and Environmental Exposure

IoT sensors are in highly aggressive environments: changing of moisture levels, corrosion, salinity, temperature, mechanical loads from farm equipment. Resistive sensors with saline swine, are corroded very rapidly, and optical probes with soils cloudy with debris can be made nonfunctional [14]. The durability issues lead to a high cost of replacement and low use by farmers.

8.2 Energy Supply Limitations

Most soil sensors rely on battery power. Frequent battery replacements are not sustainable in the remote rural field, especially when sites are buried in soil [17]. Energy harvesting (solar, vibro-kinetics, thermal gradient) is encouraging, but still experimental. LoRaWAN technologies can extend battery lives to 5+ years of life, however protocols like Wi Fi will deplete batteries within 5 days due to a high-power requirement [12].

8.3 Network and Connectivity Constraints

8.3.1 Connectivity Gaps in Rural Areas

In other instances, rural areas will not have telecom infrastructure (e.g. Sub-Saharan Africa, Southeast Asia). NB IoT and LTE M technologies rely on cellular networks [19]. LPWAN infrastructure (LoRaWAN gateways) infrastructures are also more costly for initial investments than farmers were willing to invest.

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8.3.2 Reliability of Communication

Soil IoT nodes must be transmission compliant under weather extremes. Packet loss, most related to interference or weak signal strength, would inhibit time sensitive timely insights [15]. Current research prototypes are using hybrid ZigBee + LoRaWAN combinations to meet reliability standards, but the complexity of nodes are increased [9].

8.4 Data and Platform Challenges

8.4.1 Information Overload: Farmers are not agronomists, and even less, data scientists; presenting them dashboards filled with raw numbers compounds their dilemma rather than improves their decision making [10].

8.4.2 Lack of Standardized Data: Manufacturers have different formats for data making interoperability among platforms impossible [7]. The IEEE and ISO have projects underway but are not yet in sync.

8.4.3 Data integrity and security: There is exceedingly low data encryption adoption and leaves soil data unencrypted. There is growing blockchain supported transparency logging research [15].

8.5 Economic Barriers

Hardware/subscription models are usually more expensive than farmers can afford. Even a soil IoT kit (~200-300 USD per acre sensor + gateway + subscription fees) is incredibly expensive for low-income economies [19]. For large farms competing to remain competitive means that up-front costs are acceptable because efficiencies will be realized. Smallholder smallholders are typically the ones who do not want any long-term commitment without cooperative/gov. support.

8.6 Social and Adoption Issues Farmer Trust: Agricultural systems are strongly tied into culture, and evidence-based trust systems. Therefore, the application of traditional indicators (feel soil texture, see plant health) will replace reliable systems with support of potentially new science. Awareness & Training: Gaps in digital literacy will block adoption. If Farmers are not provided some form of training on interpreting charts and reporting indices, IoT systems will fail (even if they initiated the process of receiving the system) [7]. Equity: Some smallholders in certain low-income countries will experience potential digital divide as only wealthier farmers will establish mechanization systems at lower prices than smallholders will be able to compete with pricing [10].

Table 7. Challenges and Impacts in IoT Soil Health Monitoring

Challenge Domain	Example Limitation	Real-World Impact	References
Sensor Accuracy	Drift in pH or nitrate sensors	Inaccurate fertigation recommendations	[5] [14]
Durability	Corrosion of resistive probes	Frequent replacements, high costs	[14]

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Challenge Domain	Example Limitation	Real-World Impact	References
Energy Constraint	Battery depletion, hard replacements	Downtime of sensors in remote fields	[12] [17]
Connectivity	Poor signal in rural areas	Data loss, unreliable dashboards	[19]
Cost Barriers	Expensive kits/subscriptions	Farmers unable to afford adoption	[19]
Data Overload	Non-intuitive dashboards	Farmer confusion, low adoption	[10]
Standardization	Proprietary protocols	Lack of interoperability across farms	[7]
Trust & Training	Digital illiteracy among farmers	Underutilized IoT potential	[7] [10]

8.7 Environmental Constraints

Finally, environmental limitations of IoT functionality:

8.7.1 Soil properties: despite the fact IoT networks are densely packed, "micro patch" variations will not be captured in sandy or clay soils.

8.7.2 Frontal Storms: floods, droughts, or heat waves can easily damage equipment.

8.7.3 Sustainability: E waste is a problem [creating environmental liability/costs] – large-scale placement of sensors that have short lifespan is also creating environmental risk. [18].

IoT for soil monitoring is not a silver bullet. Sensor drift, reliance on energy, connectivity barriers, cost, and adoption from other farmers, have resulted in hard limitations to scale in real-world applications. These limitations require not only better hardware but also systems thinking that incorporated or included farmer training, collective funding, and the appropriate policies. These limitations define the space for informing future possibilities and innovations which will be rest of the section.

9. Conclusion and Future Scope

The soil is not an inert medium for crops, but rather a living, dynamic systems mediate the productivity of food, biodiversity and environmental services. With increasing pressure from intensification farming, climate change and land degradation, new soil monitoring and management systems need to be developed for soil health. This review shows that an innovative soil health monitoring system is through the Internet of Things (IoT). By linking sensors, communication networks, cloud platforms, and smart dashboards, we can transform point-in-time, laboratory-based soil testing, to continuous time, site specific, actionable management. In this review, we have outlined:

• Soil Health Indicators (including physical, chemical, biological)- the possible (compatible) devices/sensors of the Internet of Things could include electronics capacitive moisture probes, ISFET pH meters, ion selective electrodes.

• IoT architectures that have been developed around a perception layer, a network layer, middleware, and application layer that provide an ecosystem with a physical edge gateway (as hardware) for interaction with cloud databases (as software) to provide a user interface and visual for a farmer.

• Communications Protocols such as LoRaWAN or NB IoT, or ZigBee or Wi-Fi all have varying reach, power consumptions, and costs.

• Cloud and analytics platforms that may be manually or purposefully created to facilitate the incorporation and/or analysis of heterogeneous datasets that include soil, with machine learning to examine soil health with predictive analytics.

• Case studies of Spanish vineyard, Indian rice fields, Dutch greenhouses, Kenyan smallholders, and coastal China which provided evidence leading to water savings, nutrient efficiencies, and models for adoption.

• Issues and challenges that include sensor drift, durability, power limitations, unreliable Rural connectivity, costs, and trust of a farmer.

• Future opportunities like Edge AI, Blockchain, data transparency, digital twins, energy harvesting sensors, and open-source cooperative models.

From the previous content, it's evident that IoT soil health management systems can improve resource use efficiencies (ex. water, fertilizer), support environmental sustainability and resilience to climate variability, but it is also Marque's vulnerabilities and system need to be cost effective, last long, produce reliable data, have interoperability, and be socially acceptable to have global relevance.

Looking forward, with the merging of IoT with AI, energy, and participatory models of farming we will see whether or not these systems remain small scale interventions or grow into commercial agriculture. While we figure this out, we also need to be aware of equity and inclusion backgrounds so that smallholders i.e. the farmers who constitute the largest share of global farmland, don't miss out on the digital agriculture revolution.

In conclusion, it is apparent that the IoT has made it through the tech hype cycle, and it is on a trajectory to serves as the telecommunications infrastructure for sustainable systems. Soils, the underlying asset of our food systems, will be increasingly managed under the moniker of "digital stewardship." Soil informed decision making enables producers to do more with less based on function, i.e., data can serve as part of insurable IoT systems, accountably regrowing researchers, to ensure future generations have soils, rich, alive and healthy soils NOT devitalized. In order for soils to have that potential, engineering, agronomy, data science,

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horticulture, and IT political scientists will need to multilayered efforts to create soil IoT to yield greater than planned productivity.

The potential of IoT is being uncovered and realizing new research challenges and limitations noted in Section 9 are hinting of new research avenues and challenges, while many other parallel technology waves particularly AI, blockchain, energy harvesting, and digital twins are all providing foundations for new transformative possibilities as IoT and Agriculture coevolve. Collectively these themes advance engagement four dominant themes of sustainable soil monitoring and flagging.

9.1 Edge AI and Embedded Intelligence

Current IoT systems basically send everything in raw form to the cloud, next generation IoT systems will be able to run edge intelligence on microcontrollers and also run lightweight analytical models on microcontrollers too, what cool things like TinyML and TensorFlow Lite Micro allow enables us to make intelligent decisions quickly possibly when internet is down [20]. Cost-Savings: less data to push up to the cloud, immediate response time, may work when offline. Example: farming decision rule on/at farm that will turn on irrigation pumps when moisture levels exceed threshold even when the cloud is not active [13]. Research Area: predictive maintenance of sensors, having our edge AI would allow to detect sensor calibration drift.

9.2 Blockchain and Data Transparency

Soil health data possesses significant political and economic value. Root IoT soil measurements underpin subsidies, certifications and compliance monitoring, and farmers being able to provide data in environmental reporting. Blockchain data can securely and transparently and verifiably store soil health data from IoT soil display. Farmer empowerment: certifying products as "sustainably farmed" based on irrefutable traceable soil data. Policy Context: governments to verify compliance with fertilizer regulations based on inputs stream. Combined IoT + blockchain pilot projects can start now - current test projects of this nature are interested in high value crop exports, and coffee and grapes.

9.3 Digital Twins of Farms

Linking Protocol Based Peat moss surrounding crop growth models is leading farmers to deliver interventions (e.g., a farmer may ask "what if I pump irrigation tomorrow?" - this would impact yield predictions.) Example: the create a digital twin of soil around a greenhouse and model nutrient leaching behaviours in response to up- or down-controlled fertigation levels. Benefit of this approach is to do some "what If" modelling without risk to a crop in the field.

9.4 Energy Harvesting and Sustainability

In this, discussion focused on recognizing how having the energy underground soil nodes can be untenable challenge. Future sources of mutually beneficial opportunities include: Solar Micro panels. Units exist as available, even field deployable, however, if the unit is shaded

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even a little, the micro-deployment, will lose efficacy - Piezoelectric harvesting. Using harvesting piezoelectric vibrations from tractor/machinery overhead, to generate a throughput of small electricity through the use of a source of energy (typically a tractor/machinery). And in Soil Thermal Gradient Harvesting - Interesting emerging research, and use the temperature differential between aboveground soil surface temperature versus soil temperature. Sustainable, well understood, ecological indicators, eco-friendly measures, are a must to mitigate ecosystem waste [18].

9.5 Multi Modal and Data Fusion

No single indicator can model all dynamic soil functions; therefore, future indicators will include fusion of indicators: Fuse ground nodes, (discrete on the ground set of instruments), with - satellite, methodical or drone, or multiple spectral methods of imaging – this will enable spatial imaging of soil conditions [19]. Fusion of ground nodes and additional sensors maybe used to predict drought stress prior to the actual onset of drought assessment - example- sensor that predicts drought stress could collect data as a soil moisture sensor with weather modelling in the fusion indicating to producers when drought stress begins.

In thinking to intersect the out of body piece we could consider particularly the spectral remote Spectro analysis to spatially scale soil parameters in eco-physiologies related areas to also other openly acknowledged parameters to identify patterns post warm insertion that may related to soil organic carbon (and explore longitudinal formations).

9.6 Open Source and Community Models

For smallholder farmers the actual price is the single biggest barrier - prototype models are latent in: Low costs kit - Holland and microcontroller $50. Cooperative co-ops - e.g. co-op owned LoRaWAN gateways, (Kenyan [19] Pilot Program, learning cooperatives). Open standards - encouraging type of product that is adaptable and potentially using plug on sensors, that is adoptable, therefore avoiding vendor lock-in.

Table 8. Future Research Directions for IoT Soil Monitoring

Innovation Pathway	Description	Anticipated Benefits	References
Edge AI / TinyML	Models embedded on microcontrollers	Reduced latency, autonomous operation	[13] [20]
Blockchain Integration	Immutable logging of soil IoT data	Trusted certification, transparency	[15]
Digital Twin Farming	Virtual farm mirror with real-time data	“What-if” scenario testing, proactive decisions	[16]

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Innovation Pathway	Description	Anticipated Benefits	References
Energy Harvesting Sensors	Solar, piezoelectric, thermal harvesting	Reduced battery replacement, eco-friendly systems	[17] [18]
Data Fusion Approaches	Combining IoT, drones, satellite imagery	High spatial coverage, improved reliability	[19]
Open-source & Low-cost Kits	Community-owned networks	Affordability, inclusivity for smallholders	[19]

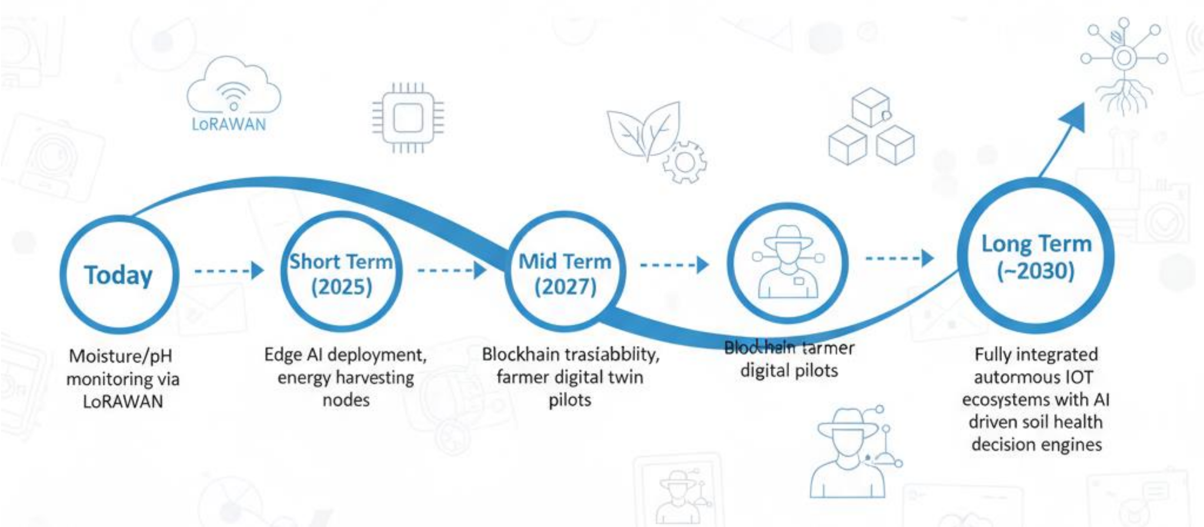

Figure 8. Roadmap of Future IoT for Soil Health

The evolution of IoT-based soil monitoring in the future is scoped out through emerging research themes and enabling technologies. This future-oriented roadmap in Fig.8 highlights probable innovations that will influence sustainable soil health monitoring including edge AI, blockchain, digital twins, energy harvesting, and open-source platforms.

Soil health monitoring through IoT is likely to change dramatically over the next ten years. Firstly, edge computing will enhance the autonomy and intelligence of the systems, while blockchain and digital twins will ensure increased analytical sophistication and transparency. Moreover, energy harvesting technology will minimize the carbon footprint while enhancing longevity, and community models will enhance equitable access. Together, these trends could ease chronic problems that are well understood now and give IoT soil monitoring the opportunity to be the global standard of precision agriculture once and for all.

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